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*Published in:*

Workshop on Adaptive Collaboration (colocated with CTS 2012)

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*Document Version*

Publisher's PDF, also known as Version of record

*Publication date:*

2012

[Link to publication in University of Groningen/UMCG research database](#)

*Citation for published version (APA):*

Capodieci, N., Cabri, G., Pagani, G. A., & Aiello, M. (2012). Adaptive Game-based Agent Negotiation in Deregulated Energy Markets. In Workshop on Adaptive Collaboration (colocated with CTS 2012) IEEE (The Institute of Electrical and Electronics Engineers).

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# Adaptive Game-based Agent Negotiation in Deregulated Energy Markets

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**Abstract**—In the emerging deregulated energy paradigm enabled by the Smart Grid, energy provisioning will change drastically. Energy contracts will be negotiated between a potential multitude of parties at high frequency (e.g., several times per day) based on local needs and micro-generation production facilities. In this context, this paper presents an agent-based approach to manage negotiation among the different parties. The goal of the presented work is to propose adaptive negotiation strategies for trading energy in a deregulated market. In particular, we provide strategies derived from game theory, in order to optimize energy production and supply costs by means of negotiation and adaptation. The novelty lies in the adaptation of the class of minority and stochastic games to the energy trading problem in order to model the strategy of the various parties involved. The paper presents also simulation results of a scenario with a large number of energy buyers, a small set of *prosumers* (energy consumers and producers using renewable micro-generation facilities) and a few large-scale traditional electricity suppliers.

**Keywords**—Multi-Agent Systems; Energy; Market; Adaptation

## I. INTRODUCTION

The *energy market* is rapidly changing: while once it was based only on traditional big energy generating companies (*Gencos*), which also had the monopoly on the transmission and distribution services, now it is opening to a very high and dynamic number of players. Most of these new players can produce smaller quantity of energy, often derived from renewable energy sources and they are all inserted in the Smart Grid. Smart Grids are digital enabled nets of energy consumers, suppliers and *prosumers* that are able to optimize energy provisioning also by introducing a flexible approach for short-term contract stipulation. A *prosumer* is a domestic environment (therefore it is a *consumer*) provided with micro-generation facilities, such as solar panels, small wind turbines, combined heat-power generation. Its surplus energy production may be sold to neighboring consumers (therefore it is also a *producer*). Due to the market shift from long term energy contracts to higher granularities, we see the need for adopting an autonomous system able to represent the end user's needs, both for energy sellers and for buyers. In fact, the user can hardly take care of her energy requests manually several times a day while busy in everyday activities. Thanks to their

autonomy, software agents are one of the best candidates to accomplish this task on behalf of users; a MAS (Multi Agent System) can include buyer agents representing the ordinary energy consumers, specific designed *prosumer* agents able to contract for incoming/outgoing electric energy flow, and agents acting on behalf of big energy producers. Every agent will need to be instructed on the possible actions to take during the negotiation rounds and they will have to learn how to adapt to the market dynamics. Adaptivity is defined as a property that enables participants of a system to sustain themselves in such dynamic environments [1]: in our work, the participants are the agents with their respective roles in an ever changing electricity market. This paper focuses on the negotiation and adaptation aspects: how can we instruct every single agent in a MAS in order to achieve better priced contracts according to the user's expected budget? The two kinds of energy sellers (*Gencos* and *prosumers*) adopt two different price strategies: the former ones rely on a fixed but higher price, while the latter ones can propose cheaper but changing prices. Even if this makes the scenario extremely complex, we want to model its negotiation in a simple way by reducing it to elementary steps that we can link to specific topics of game theory. In fact, the multitude of agents could represent a game with a plurality of participants, while the high granularity of contracts implies different negotiating rounds that can be linked to the game theoretic concept of repeated game. An evaluation of each negotiation enable agents to learn from it and to adapt the next one. Our approach uses different concepts of game theory like *minority* and *stochastic* games creating a new and difficult to analyze scenario, thus more prone to be studied through *simulation*. In a previous paper, we interfaced a JADE implementation with a physical smart meter installed in a home, in order to investigate the feasibility of an agent-based approach [2].

The paper is organized as follows: Section II provides a brief description of previous related work, while the description of the proposed agent architecture follows (Section III), along with with the proposed game theoretic approach (Section IV). We then provide in Section V a detailed description of the performed simulations involved in proving the efficiency of the proposed models and strategies. Concluding comments and

remarks follow in Section VI.

## II. RELATED WORK

Game theory is a well established field with a vast literature. More details about the rigorous formulation of the game theory problem, definitions and notations commonly used in this work can be found in Layton-Brown and Shoham work [3]. For retrieving deeper knowledge on repeated games, see for instance [4], while the reference example of minority game used in solving the presented problem has been already investigated in [5], [6]. The following sections will make clearer to the reader how the work about the “El Farol Bar” minority game problem is strictly connected to our approach in finding equilibria. Insights of these notions combined to multi agent systems and their applications (e.g: negotiation techniques, auctions, ...) are excellently explained in many other books: [7] is a very famous example on the topic. Game theory and energy related issues together are not completely new: in [8] Ramchurn *et al.* describe a decentralized agent approach for avoiding energy consumption peaks, achieving less polluting emissions and average lower contract prices using all the features a Smart Meter can offer. In order to evaluate and forecast the percentage of Smart Meter users in the net, they used some concepts of evolutionary game theory. Vytelingum *et al.* in [9] used the game theoretic approach in order to find the Nash equilibria to determine when an agent inserted in a Smart Grid is supposed to use a previously stored amount of energy or to obtain electricity from the grid. On the other hand, our solution relies on the fact the buffering and/or storing electric energy is difficult and expensive to achieve, and it hardly fits the short-term approach to the market. Fuzzy logic and negotiation is also a recurrent topic in previous researches [10]: in a way not so different from our approach, it is used to help agents to adapt to the ever changing conditions of the e-market. Also, in Jia-Hai *et al.* a fuzzy logic approach was used to describe their model for the decentralized market [11]. This latter work is well completed with the addition of several reinforced learning techniques and the benefits for the usage of the game theoretic approach is seen as computationally intractable. In our work we want to use different approaches to prove that a model with mixed point of view can indeed provide satisfactory results.

## III. AGENT ARCHITECTURE

An agent-based architecture can be used to describe an energy market scenario with a large number of energy buyers, a small set of *prosumers* (energy consumers and producers using renewable energy sources), and an even lower number of big electricity suppliers (*Gencos*). Those entities interact with each other during several short-term negotiation rounds in which the purpose for the sellers is to sell energy contracts, while consumers have to obtain an energy contract as cheap as possible. Each participant in the market can therefore be represented by a software agent, and the negotiation mechanism is the auction (apart from *Genco*’s fixed price). Three

different kinds of agents are involved in the negotiation: *Buyer*, *Prosumer* and *Genco*, while a fourth kind, *Balancer Agent*, is not involved in the negotiation, but it helps in synchronizing operations and in load balancing duties. Let us consider each one individually.

**Buyers** are energy consumers; they do not produce energy so they are searching for electricity by stipulating contracts related to a specific time interval. Each market day is divided into several time intervals and for each one every buyer has to decide in advance who is going to be its energy supplier for the next time interval. In the developed software simulation, every day is composed of six time intervals and a *balancer agent* to a certain extent controls the amount of energy exchanged in the negotiation process (the details are explained later in this section). Buyers can predict how much energy they need for the following time interval. This can be obtained by reading previous electric measurement and by applying an energy consumption forecasting algorithm. It is important to perform this forecast before any negotiation, so that the buyer can choose the most suitable seller according to the energy availability of the available suppliers. A really effective forecasting algorithm that fits our short-term paradigm is thoroughly described in [12] and it is based on an adaptive two-stage hybrid network with a Self-Organized Map (SOM). Every buyer is in competition with other buyers: each consumer has the goal to stipulate the cheapest contracts by either winning an auction handled by *prosumers* or by choosing the right time to stipulate a contract with the cheapest *Genco*. While these actions clearly underline a *competition* between agents, *adaptation* techniques will be performed at the end of every negotiation round in order to follow the possible market variations over time (i.e. price fluctuations).

**Prosumers** produce and consume energy; they produce a smaller quantity of electricity compared to *Gencos* by using renewable sources of energy. If the amount of energy is more than what they consume in a given time interval, they may decide to sell surplus electricity to other neighbors (buyers). *Prosumers* have also information about weather conditions in order to have a forecast on the amount of energy that will be produced (an example on how to automatically retrieve weather forecasting information is by using existing web services).

### *Prosumer hypotheses:*

- A buyer can stipulate a contract with a *prosumer* after winning an auction round, based on sealed bids; every buyer sends different offers to a suitable *prosumer* (Dutch auction)<sup>a</sup>
- Once the investment in a small-scale energy production plant based on renewables is realized, any positive amount derived by selling energy contributes to the

<sup>a</sup>Actually, in the literature there are different definitions of the Dutch auction. In this article with “Dutch auction” we mean an auction system in which sealed bids are sent to the seller: buyers do not know any bid values of the other consumers.

investment return. Therefore in order to be attractive, *prosumers*' starting prices can be considered as substantially lower than *Gencos*' initial contract prices.

- Weather conditions during an observed interval can prevent a *prosumer* to generate enough electricity to be sold.
- *Prosumers* communicate to buyers an initial starting price that is influenced by contracts with energy Transmission System Operators (TSO) and Distribution System Operators (DSO) and a random cost due to the devices used to produce electricity (e.g., maintenance costs).
- The energy produced by a *prosumer* has to be sold and cannot be stored or buffered.

Every *prosumer* is in direct competition with other sellers: they have to propose an appealing starting price and make an intelligent use of refusing bids in order to rise the price and, at the same time, avoid pushing buyers in contacting other sellers.

**Gencos** are big energy generating companies. They have a theoretically infinite amount of energy supply, but sold at a fixed price, so there is no auction negotiation and every contract can be stipulated much faster compared to the *prosumers*' auction system.

*Genco hypotheses:*

- *Gencos* prices are higher than *prosumers*' starting price.
- *Gencos* prices depend on TSO/DSO contracts, raw material price and (most important in our scenario) threshold exceeding costs. This aspect is thoroughly explained in the following paragraph.
- A *Genco* receives a request from a buyer; then it just calculates the price according to the above-explained variables and communicates the final price back to the buyer.

**Gencos threshold system:** A key point is how much energy a generating company can produce without having to buy some of it on the market (e.g., a foreign and more expensive market). So we assume that every *Genco* has a supply *threshold*, and once reached, the *Genco* has to buy energy abroad (the energy production of that seller is under stress). So the energy cost can be calculated as follows:

$$C_u = \begin{cases} Cost_{energy} & \text{if below supply threshold} \\ Cost_{energy} + (EC \times A) & \text{if above supply threshold} \end{cases}$$

where  $C_u$  is a single energy unit cost,  $EC > 1$  is an external cost constant and  $A > 0$  is number of energy units above the threshold.

Surpassing the threshold might also be harmful for the environment since more polluting plants might be started (e.g., oil based). Asking the *Genco* for contracts when this threshold is already surpassed leads to more expensive contract prices. Those prices rise as we get further from the specified threshold. This particular pricing strategy already introduced in [2] is perfectly compliant with the findings of other researches: from the already cited [8] and [9] to older studies led by Brazier *et al* in [13]. These researches do not provide the

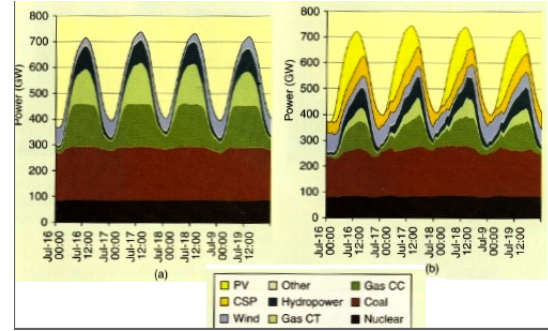


Figure 1. U.S. Nationwide energy dispatch without (a) and with (b) renewable contributions. Source [14]

same formulation, however the common conclusion is that higher satisfied demands will stress energy production lines introducing additional costs for the final user.

*General hypotheses:*

- A balancer agent keeps track of how much energy *prosumers* can supply; subtracting this amount from the total energy demand in an observed area should give an idea about the quantity of energy that *Gencos* have to produce. Dividing this quantity by the number of functioning *Gencos* gives an advice on how many energy units every *Genco* is supposed to produce in order to not generate more energy than needed.
- Even in this case, storing or buffering energy is not a viable solution.
- The threshold is calculated according to the demand forecasts. It also depends on the maximum capacity for *Genco*'s energy production lines.

The **Balancer** agent is responsible for the synchronization of negotiation procedures and for the balancing aspects: it acts in the very first step of the negotiation round by retrieving the single demand of every consumer and the production forecasts of the *prosumers*. Since producing more energy than needed is not convenient to anyone, agents here are collaborating to avoid useless energy production; this can be obtained by notifying the *Gencos* about a suggested amount of energy they should produce taking into account the previously introduced notions of demand and *prosumer* supplies. Recent studies [14] have shown how the nationwide energy dispatch will react to the introduction of renewable sources; in particular, the energy production derived from traditional sources will decrease: in the U.S.A a future projection of four summer days in year 2030 is depicted in figure 1 and shows two scenarios, with and without solar penetration and how their percentage of produced energy compares to traditional sources. The demand satisfied by the total production from all sources remains constant in these two scenarios; however, in (b) we can see how the introduction of PV and CSPs (respectively PhotoVoltaic and Concentrating Solar Power plants) will cause decreasing in production by all the traditional suppliers.

The data in figure 1 refers to GridView<sup>b</sup> production cost model, with hourly load, solar and wind projections for 2030 based on 2006 information to maintain data correlation. On a separate note, it is important to point out in figure 1 that solar plants have production peaks during central hours of the examined days.

#### IV. ADAPTIVE AGENT NEGOTIATION

The provisioning and selling of energy can be modeled as a game in which each agent's goal is to make an economic profit. A round of the game is the negotiation of energy during one time interval in which each market participant (in our case software agents acting on behalf of human users) may have a certain probability to win or lose, according to the retrieved payoff at the end of the specified round. An agent is winning when it manages to obtain an energy contract at the lowest price possible. This situation implies that agents are rational. In this context, reaching a Nash equilibrium [15] means that we have found the right strategy (or the combination of mixed strategies) that each agent does not want to change, independently of which strategies other agents have chosen. We now may want to start from an already proposed game theoretic scenario and then adapt it to fit our needs.

##### A. El Farol Bar game

"El Farol Bar" is an existing bar situated somewhere in New Mexico (USA). Every Thursday night it delivers Irish parties with discounted beer prices, becoming really appetizing for the local potential costumers. Every person living near that bar, wants to go there on that particular night. The bar has been used to model the El Farol Bar minority game [5], [6] in the following way. Given  $N$  as the population in the nearby area, and a threshold  $T$  of people attending the Irish night event, the night at the bar is considered as enjoyable if the number  $n$  ( $\leq N$ ) of participants during a particular Thursday is below the threshold  $T$  (win situation). Otherwise, it is better for the single person to remain at home (lose situation, the pub is too crowded). That is why it is called a minority game: we have two different behaviors and a single agent can win if it chooses the path taken by the minority of the population (Table I).

The similarity with our problem is given by such two-paths way of thinking: if every agent contacts *Gencos*, it results in overloading the production lines of these big energy producers, causing them to provision in more expensive markets with high prices for the end-user and environmental issues too. Likewise, if every agent contacts (or tries to do so) the same restricted set of *prosumers*, only a few number of participant gets a nice deal, due to the fact that a *prosumer* can deliver a little amount of energy, especially compared to a *Genco*. In addition, in the bar game participants are competitive and they are not able to communicate with each other, so they cannot organize themselves in order to create some sort of shift, in which they can split and choose (for a fraction of them) not to go on this

TABLE I  
EL FAROL BAR PAYOFF MATRIX

Action	Crowded Bar	not Crowded Bar
Attend	L	H
Do not Attend	M	M

With payoff score  $H > M > L$ , with M unconditioned.

Thursday, but go to the next one instead. There are similarities also here: energy bidding agents cannot communicate in this way, and they have to guess how other buyers are going to act. In the bar dilemma, there are different payoffs according to the result of each game round: a participant gets the highest score by going to the bar and he discovers that it is not crowded. He gets a medium amount of points if he chooses to stay home, and he gets a penalty (or the minimum score) in case he chooses to attend the Irish night and finds it crowded. In our problem, this score system can be replaced by the difference between what a single agent expected to spend and what it actually spends at the end of the negotiation interval.

A simple way to find an equilibrium for the El Farol Bar game has been proposed originally in [5]. We begin by illustrating this first intuitive approach. According to the demonstration in [5] there is a unique symmetrical mixed strategy solution:

$$\frac{M - L}{H - L} = \sum_{m=0}^{T-1} \binom{N-1}{m} p^m [1-p]^{N-1-m} \quad (1)$$

Where  $p$  is the probability to go at the bar and  $M$ ,  $L$  and  $H$  the payoffs as shown in Table I.

Following studies (i.e., [6]) have shown other solutions, which are classified according to fairness and efficiency measures. Here we propose a variant meeting the fairness requirement and having an average efficiency, since we do not want to compromise the fairness of the market (it would be illegal to give privileges to some buyers, penalizing others). In particular, the other proposed solutions suggest the use of fictitious play agents in order to reach a more efficient average outcome over a sacrificed fairness. An approach that has both fairness and efficiency requirements satisfied, is represented by a Q-Learning strategy in which a central authority (e.g., a major) introduces entrance fees for customers attending the bar to be distributed to the players who are at home. Even this last solution is not in line with our problem since we are describing a *decentralized* approach. Using the equation 1, we can see that for each participant we have a given probability that can be used to decide whether it is advisable to attend the Irish night. Repeating the game we can see that every agent sooner or later will attend the bar and that most of the times, the pub will not be so crowded. When trying to apply the solution shown in the equation 1 to our energy problem, we map some variables as follows:  $T$  for the ratio between the amounts of energy produced by *Prosumers* over the *Gencos*,  $N$  is the total number of buyer agents and  $M$ ,  $H$  and  $L$  are intervals defined according to the expected/actual money spent. A difference between the bar game and our

<sup>b</sup><http://www.abb.com/industries/>

Let  $\mathcal{J}$  be a set of agents representing the consumers;  
 $\mathfrak{P}$  be the set of prosumers, while  $\mathfrak{G}$  represents the  
Gencos;  
Players  $\in \mathcal{J}$  move through different tables shaping the  
*finite state space*  $\mathcal{M} = \{m_0, m_1, m_2, m_3\}$ .  
 $m_0$ : initial state in which the agent  $i \in \mathcal{J}$  decides who  
is going to first contact. It can be a Genco or a specific  
Prosumer  $P_0 \in \mathfrak{P}$ .  
 $m_1$ : second state in which  $i$  decides who will be con-  
tacted next, provided that  $D(i) > S(P_0)$  with  $D$  being the  
consumer demand and  $S$  is the seller's supply capacity.  
 $m_2$ : here  $i$  decides if it is convenient to place a bid to  
a previously contacted prosumer  $P_x \in \mathfrak{P}$  or abort the  
negotiation, provided that  $D(i) \leq S(P_0)$ .  
 $m_3$ :  $i$  decides to accept or not the offer of a specified  
Genco  $G_x \in \mathfrak{G}$ .  
Therefore each player (agent)  $i \in \mathcal{J}$  can perform an  
action inside the set(s):  
 $\mathcal{A}^i(m_0) = \mathcal{A}^i(m_1) = \{\text{Contact Genco, Contact Pro-}$   
 $\text{sumer}\}$ ;  
 $\mathcal{A}^i(m_2) = \{\text{Place bid, Abort Negotiation}\}$ ;  
 $\mathcal{A}^i(m_3) = \{\text{Accept offer, Refuse offer}\}$ .  
The probability  $P$  to move from the current state  $m_x$  to  
next state ( $m_y$ ) after performing a specific action  $a \in \mathcal{A}$ ,  
written  $P(m_x, a, m_y)$  is described in Tables II, III, IV  
and V with their assigned payoff chains.

Figure 2. Game formalization.

energy market is that in the bar game if a number  $m$  of  
people are attending the bar with  $m > T$  then  $m$  players are  
losing. In our problem just  $T - m$  people are actually going to  
retrieve a low payoff. This initial model still lacks of influential  
variables like time constraints and limited *prosumers'* supplies,  
implying the necessity of adding further stages to our game.  
We now present an approach in which several tables represent  
different payoff matrices for all the stages forming the game.  
This *new* methodology that mixes the minority game approach  
with a stochastic game (every payoff table refers to a specific  
participant's state) is used in order to model the complexity of  
the energy problem. The main idea behind the adaptation of  
the game we propose is presented more formally in Figure 2.  
It is an infinite game split into finite rounds. The decision  
each agent takes at every state is compactly represented in the  
following payoff tables.

Tables II and III are called *initial state tables* while Ta-  
bles IV and V are defined as *final state tables*. The difference  
is that only Tables IV and V show an ending of the negotiation,  
represented by the letters  $H$ ,  $M$  or  $L$  as the payoff entity inside  
those cells.

Every buyer starts by taking a decision in the first table  
(referring to an element of the state space  $\mathcal{M}$ ). The balancer  
agent is the entity that knows how much energy can be  
produced by all the *prosumers* and by using this information

TABLE II  
INITIAL STATE 1 (TAB<sub>1</sub>)

Action	P. has supplies	P. has no supplies
Contact Pros.	See TAB <sub>3</sub> (+2 Ip)	See TAB <sub>2</sub> (0 Ip)
Contact Genco	See TAB <sub>4</sub> (+1 Ip)	See TAB <sub>4</sub> (+1 Ip)

TABLE III  
INITIAL STATE 2 (TAB<sub>2</sub>)

Action	P. has supplies	P. has no supplies
Contact other P.	See TAB <sub>3</sub> (+2 Ip)	See TAB <sub>2</sub> (0 Ip)
Contact Genco	See TAB <sub>4</sub> (+1 Ip)	See TAB <sub>4</sub> (+1 Ip)

it can calculate the number of buyers that could be served by  
*prosumers*; this number can be related to the threshold  $T$  in the  
El Farol game. According to that threshold we can calculate  
the probability to contact *prosumers* instead of a *Genco* in  
this stage of the negotiation (quite similar to how it was  
possible to solve the “El Farol Bar” dilemma using the unique  
mixed strategy solution). However, at this moment we do not  
have a clear vision of future payoffs, but we can assign to  
those initial tables a certain amount of fictional points that we  
call “Intermediate points” (Ips). Those Ips represent the chain  
of payoffs for the stochastic game approach: assuming that  
every action taken by a participant agent is time consuming,  
decreasing Ips simulates time flow as well as a risk increase  
that the participating agent should be aware of. Risk awareness  
in auction bidding systems has already been studied [16];  
although the concept of risk is elaborated in a different kind  
of market model, a risk-aware agent better simulates how a  
human user would act. On the other side, higher Ips increase  
the chance to have a satisfactory game result (H or M final  
payoff). In this way the buyer is redirected to other tables until  
it reaches a final cell: doing so the number of Ips can increase  
in case it is a lucky choice (contacting a *prosumer* that for sure  
has enough supplies) or decrease in the opposite scenario. In  
the *initial state tables* the buyer is redirected to other tables  
according to a previously calculated value that is related to  
the amount of energy all *prosumers* can produce. In the *final*  
*state tables* the algorithm is different: in order to simulate the  
importance of the time variable, lower Ip values mean that the  
buyer has been traveling around different tables for such a long  
time and chances to find a suitable seller or even a *Genco* that  
has not overtaken its threshold will be scarce. That is because

TABLE IV  
FINAL STATE 3 (TAB<sub>3</sub>)

Action	Pros. accepts	Pros. refuses
Place bid	<b>H</b>	Stay in TAB <sub>3</sub> (-1 Ip)
Abort negotiation	See TAB <sub>2</sub>	See TAB <sub>2</sub> (0 Ip)

TABLE V  
FINAL STATE 4 (TAB<sub>4</sub>)

Action	Genco above T.	Genco below T.
Accept genco's offer	<b>M</b>	<b>L</b>
Refuse genco's offer	See TAB <sub>2</sub> (-1 Ip)	See TAB <sub>2</sub> (-1 Ip)

in the ending tables negative values are present. When the  $I_p$  value is very small ( $\ll 0$ ) then the agent is forced to get a contract with a *Genco* in order to avoid wasting other time (and consequently other money). At the end of each round, each buyer agent evaluates its outcome. Above we said that the difference between the expected money spent and the actual money spent can point out who are the winners and who are the losers, but the situation is more complex. Let us consider for example a buyer agent ending a negotiation round having obtained an  $H$  (high) payoff: how can our system verify that this supposedly high utility gained corresponds to a cheap contract? As long as the money spent is equal to the desired agent budget the answer will be positive, but this case has to be applicable to a very dynamic scenario in which market prices (i.e: raw material, introduction of new TSO/DSO competitors) can constantly change over time. If an  $H$  payoff corresponds to an amount of actual money spent significantly higher (lower) then the budget, it means that, according to the market, the agent was expecting an unrealistically low (high) price for energy unit. Here lies the need for finding an adaptation method for calibrating bids and budgets according to the price swings of the real market. In Section IV-B, a fuzzy logic approach will be described. Those kinds of logics are recurrent in negotiating strategies since they are able to model factors not only related to human behavior (like the seller patience factor in [10]) but also for balancing and distribution [11].

### B. Adaptation from Previous Bids

Agents should improve their performance as they act in the market. Therefore, they should adapt to the market trends and also to the way other agents are performing. Each buyer initially has the following variable parameters that are subject to change during the subsequent rounds:

- An expected amount of money he desires to spend for an energy unit;
- A certain number of refuses to receive before deciding to change seller; and
- A certain amount of money representing the rising of the stake after each bidding refusal.

While each *prosumer* has:

- An amount of money he desires to earn after a negotiation; and
- A certain number of refuses to give if the buyer bids are lower than the expected gain.

Every buyer sends a sealed bid to the *prosumer*. The *prosumer* therefore checks for the highest bid and refuses everything else; then if the highest bid is satisfying, it may decide to accept the contract, otherwise it refuses also the highest bid and waits for every buyer to send it other sealed bids that will be higher than the previous ones, in an iterative process. A certain buyer has a limited amount of times in which it sends offers, after which the stakes are too high so that it will consider other sellers. From the buyer's point of

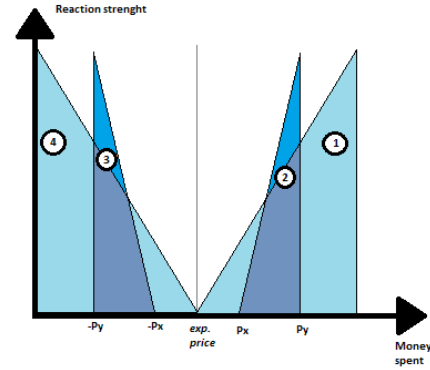


Figure 3. Controlling bids diagram. Buyer's side: 1) Increase expected money to spend, 2) Rising stakes/bids, 3) Decrease Rise stakes/bid, 4) Decrease expected money to spend.

view, we need an adaptation strategy that can adjust its variable parameters in order to succeed in this auction bidding system. The more its spends, the stronger will be the autonomous reaction that will influence the variable parameters in order to contrast the unwanted trend (a graphic representation is given in Figure 3).

The graph depicted in Figure 3 is centered in the expected money to spend. If the spent money is surpassing the right interval, then the system reacts by slowly rising the stake of every single bid and increasing the spending expectations. On the other side, if the value for money spent is located in the left side of the graph, the reactions will be the contrary compared to the last situation: this is done in order to adjust expectations in the case of lowering of market's prices for electricity.

In summary, the strategy of the buyer is captured by the following four steps.

- 1) Before the negotiation, according to *prosumers'* production threshold, every buyer starting from the first initial table immediately decides to contact a *Genco* or a *prosumer*.
- 2) The buyer follows every needed redirection across the four strategy tables. Every choice depends on how many intermediate points the single buyer has accumulated.
- 3) After the negotiation, if the buyer has a supposed large number of Ips, but still it ended up in a M or L cell and its money expectation are not met, then the agent has to learn from that, changing the way the buyer travels across the tables according to the Ips.
- 4) The examined agent applies the mathematical functions that we can extract from the fuzzy styled control system graph shown in Figure 3.

## V. SIMULATION

We developed a simulation environment featuring 100 buyer participants, 10 *prosumers* and 5 *Gencos* over 400 negotiation rounds. The goal of this simulation is to test efficiency, that



is, a measure of collective agent utility achieved relative to its maximum value [6]. Specific to our case, the utility is represented by the money spent. Therefore we should adjust the previous definition by pointing out that the sum of money spent by a single agent is compared to the minimum average energy contract price calculated in all the examined rounds. The simulation was executed on a computer with AMD Athlon II Dual Core M300 2 GHz processor with 6 GB RAM running a Windows 7 64 bit edition operating systems and a Java virtual machine environment JAVA SE 6 Update 21 [17].

Several parameters can be adjusted influencing the final strategy, namely: (1) the number of Ips used as threshold in order to redirect the participant from one final table to the other; (2) the difference between starting prices for the two kinds of sellers; (3) all the unspecified values in Figure 3 that represent ranges in which different reactions are applied in order to change the agent's stake entity and/or its expected price; (4) the best way to assign values to  $H$ ,  $M$  and  $L$  final payoffs; (5) the price dynamics from one round to the other; (6) the *Gencos*' price penalties for exceeding thresholds; (7) the probability for a *prosumer* to become more expensive than a *Genco*; and (8) the accuracy about energy supply and demand forecasting that might not be 100% correct.

The best way to give precise values to these parameters is to study an analytical formulation in which we can combine all other known values (e.g., number of participants and amount of demands and supplies) in order to retrieve the unknown data. However, we decided to use a numerical approach instead, by trying several value combinations of every input variables of the algorithm. This is due to the complexity of the whole examined scenario as well as its potential to be extremely dynamic (e.g: price, agents number and demand can vary from one round to another).

At the end of each round, the program calculates the average expecting budget and the average money spent, assigning to each round number those other two values (e.g., round #, Paid Price, Expected Price). In order to have a clearer idea of the efficiency and precision of the strategy, we show the difference between applying the market strategy or adopt a baseline behaviour. In the latter scenario, every buyer will contact a *prosumer* straightaway and after signing a contract, the participant skips the adaptation phase described previously. We obtain the results shown in Figure 4, under the following conditions: (1) intersection between average starting prices of the sellers should not exceed 33%; (2) slow and not exaggerated price swings between each round; (3) significant price penalties for exceeding *Gencos*' threshold; (4) the higher the error percentage between the forecast demand values and the actual requested values (negative error), the better becomes the improvement between using the adaptation strategy compared to the baseline scenario. Positive errors may worsen participant performances; and (5) very fast reaction to follow the expected price: the intervals shown in Figure 3 should have a very small size. The conditions (1) and (3) force the gap

between the prices to be wide enough to justify the minority game approach, while (2) and (5) deal with the difficulty of the algorithm in finding equilibria in exaggerate dynamic scenarios. Finally, (4) is straightforward.

In the simulation, the expected price starts from 0 in the first round, and the convergence between the expected price and the paid price starts in the range of 11<sup>th</sup>-21<sup>st</sup> round. Economically speaking it means that in earlier rounds a buyer agent adopting the algorithm with the described strategies is likely to pay equally or slightly more than an agent following other strategies. However, if we consider a sufficiently large number of rounds, the saving is guaranteed compared to agents that always choose the strategy that immediately appears as the most convenient (Figure 4). The test was executed having a constant numbers of agents, although sellers' supply capacity was subject to randomized swings from one round to the other. Therefore, changing sellers' number does not drastically affect the presented results, provided that this number does not exaggeratedly and unrealistically change in a short period of time. In a more complex scenario in which sellers adopt strategies according to the economic background, the presence of different market competitors will determine an additional factor that needs to be further investigated in order to provide a more realistic model.

Computationally wise, the complexity of the presented algorithm is variable but does not appear to represent a problem. While the balancer agent has the duty to solve the equation 1, buyer agents just have to solve an iterated amount of conditional instruction and comparing variables (e.g: if current Ip value is greater than the threshold value then execute action A, otherwise jump to action B). The fuzzy logic block is just composed of a mixed set of linear functions and it is executed just once at the end of the negotiating round. On a separate note about the architecture itself, further tests and improvements on performances (also in a distributed net) are considered in [18].

## VI. CONCLUSIONS

In this paper we have presented an agent-based approach for deregulated energy markets, focusing on negotiation and adaptation strategies that have their root in game theory. Specifically, we exploited the concept of *minority game* to provide a better distribution of the available resources, and we used a *stochastic game* design to simulate time flow and risk variation through an accurate intermediate payoff accumulation during the same negotiating round. We have implemented a simulation of the system to test its efficiency and to evaluate the behavior over multiple rounds, on the base of a previous experience with physical smart meters connected to user homes [2]. The results show that this approach reflects real market scenarios as well as the proof that agents that adopt the adaptive strategy have better chances to stipulate cheaper contracts on average. As shown in the graph in Figure 4, the gap between the two situations (i.e., agents following the



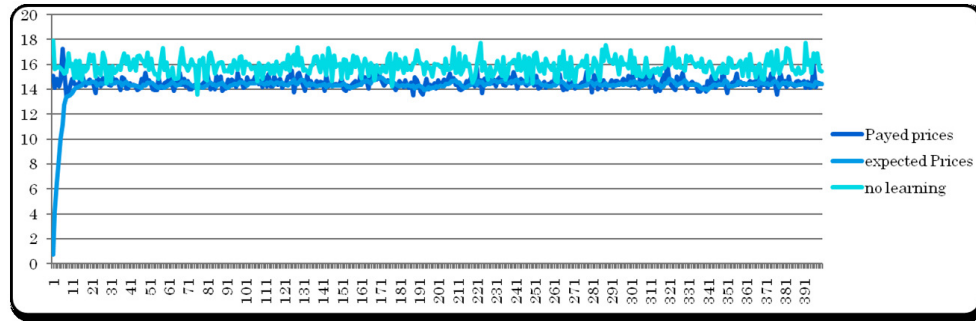


Figure 4. Three functions showing the difference between no learning prices and the chasing of expected prices with obtained average deals when using the explained strategy.

adaptive strategy and agents always contacting cheaper sellers first) is remarkable when certain conditions are satisfied. In addition to that, we can see how expected prices, starting from very low (and impossible to obtain) values tend to reach an equilibrated amount that represents the cheapest alternative in almost all the examined negotiation rounds. The prices obtained with the proposed strategy follow really close that value. Opportunistic agents that always try to win *prosumers'* auction may have some chance to win during the initial rounds, but still the algorithm provided tries to establish a Nash equilibrium nonetheless; once the prices are balanced, chances to obtain the best bargain are going to be sporadic for those agents. This strategy and these simulations help to prove that a fully deregulated market with an appropriate tax and incentive policies should help the introduction of small energy producers (based on renewable sources) able to fulfill the needs of their neighborhood. This will allow buyers to choose between different sellers with different prices, with the consequence that average contract costs will stabilize to a slightly swinging value but still towards a convergence to a value that is supposed to take place in middle of *prosumers'* starting price and *Gencos'* fixed price (when their production stays below their threshold). This convergence applied to similar dynamic and variegated scenarios has already been studied in earlier works [19]. We leave open for future investigation a more formal description of the model taking into account all the necessary variables (participants number, Ips state changing triggering values, fuzzy function values etc.) to consolidate the simulation results presented here. This includes the study of the existence of equilibria in such dynamic and complex scenarios and also additional comparative evaluations with other possible market models are needed.

#### ACKNOWLEDGMENT

The work is partially supported by the ASCENS project (EU FP7-FET, Contract No. 257414)

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